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The Corporate Economic Performance of Environmentally Eligible Firms Nexus Climate Change: An Empirical Research in a Bayesian VAR Framework

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Abstract: Corporate economic performance and its association with carbon emissions has been the subject of extensive research within the last few decades. The present study examines the economic performance of green firms as reflected in the Financial Times Stock Exchange Environmental Opportunities Index Series (FTSE EO) and its association with carbon emissions, incorporating the role of two more indices, namely the Baltic Clean Tanker Index (BAIT) and EUR/USD exchange rate. The methodology employed is the Bayesian Vector Autoregression Model (BVAR). Our findings confirm the interlinkages among the variables studied. More specifically, based on impulse response analysis, the direction of causality is two-way. The response of carbon emissions to a shock in the other variables is negative for the case of the EUR/USD exchange rate and Baltic Clean Tanker Index (BAIT) (an index representing the conventional energy sources), while it is positive for a shock in the FTSE EO. However, the most important finding is the return to the steady state after nine or ten periods. This result is very significant since the global environmental agreements along with the global economic conditions and the energy resources may well lead to limitations in carbon emissions within a framework of a well-organized and targeted climate change mitigation strategy.

Keywords: economic performance; carbon emissions; Bayesian VAR; BAIT; FTSE EO

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1. Introduction

The concentration of greenhouse gases has raised global concern and is posing unique challenges to life on Earth due to links to global warming, a fact that may well interpret the extended use of carbon emissions (CO_2) as a proxy for environmental pollution [1,2]. More specifically, the increasing emissions according to [3] have led to the following results: increase in global temperature by 1.9 F since 1880, sea levels by 178 mm over the past 100 years and carbon dioxide to 413 ppm in air, which is the highest in 650,000 years.

Within this regime, numerous initiatives have been taken by firms, governments and economic agents in order to achieve sustainable development. The concept of sustainability involves three different dimensions, namely environmental, social and economic (Zum'a et al., 2022) [4]. For firms, pursuing the concept of sustainability leads to financial pressure as adopting sustainable environmental practices is a high-cost process turning their adoption into a major concern for the managers (Zum'a et al., 2021) [5]. One solution provided in the modern literature is lean manufacturing that may well achieve an increase in productivity and reduction in operating costs, securing a raise in the three-dimensional performance, including economic, social, and environmental [4,6] (Liu et al., 2020).

The present work studies the economic performance of environmentally eligible firms in global terms since it uses the EUR/USD exchange rate, BAIT and FTSE EO to reflect the economic growth generated by renewable and nonrenewable energy sources while carbon emissions reflect the environmental degradation. The variables included were the novel element of the present work, while the Bayesian VAR is also a methodology not previously used in the particular scientific field of interest. This study is an attempt to examine the interlinkages between carbon dioxide emissions and financial indexes.

The remainder of this study is organized as follows: Section 2 provides the methodology employed, Section 3 the results and Section 4 a discussion of them. Finally, the conclusions, along with limitations and recommendations for future studies, are presented in Section 5.

2. Literature Review

The interlinkages between economic development and environmental degradation have been the subject of extended study within the last decade, revealing an abundance of significant policy implications at regional and global levels. In carbon-based (developed and developing) economies, it is a stylized fact that due to economic development, despite the efforts to improve living standards and increase the prosperity of society, the environmental degradation caused mainly by high energy consumption cancels them out. Based on a report of the Intergovernmental Panel on Climate Change [4], in the year 2019, the highest value of atmospheric CO_2 concentrations has been recorded within the last 2 million years, with the concentrations of methane (CH_4) and nitrous oxide (N_2O) also at their highest within the last 800,000 years. More specifically, the increases recorded in carbon emissions exceed the proportion of 47% compared to the multi-millennial changes noticed between the glacial and interglacial periods over at least the past 800,000 years since 1750 [4,5].

New findings and studies regarding climate change have raised public awareness towards the environment. This has been an ongoing situation for more than half a century [6,7].

The aforementioned stylized facts have generated a strand of literature by using theoretical and empirical models on the relationship between carbon emissions and economic growth in macroeconomic terms. Starting from [8], along with [9,10], empirically inverse relationships in a form of U between per capita environment pollution and per capita income have been found, known as the Environmental Kuznets Curve hypothesis (EKC).

Since then, different studies have been conducted concerning developed or developing countries with different methodologies and conflicting results [11,12]. The interpretation of those results may be attributed either to the stage of economic development and/or the level of technological innovation [11–15]. In addition, the EKC hypothesis has been expanded with different exogenous variables over time. Energy consumption [16,17], urbanization [18–20], economic development [21], renewable energy sources [22], trade opening [23,24], public expenditure [25] and tourism revenue [26,27] have been included in the analysis of empirical studies.

In terms of methodologies, the neuro-fuzzy inference system (ANFIS) model, and different cointegration techniques with ARDL and NARDL, are a few examples extensively used in time series, while in terms of panel data analysis, PMG- ARDL, FMOLS and DOLS have generated another strand of literature with different results [28–31]. In addition, in time series analysis, the causality tests and the VECM have also been extensively used in the effort to identify and quantify potential interlinkages among the variables employed [32–35]. Last but not least, it is worth mentioning the TVP-VAR (Time-Varying Parameter-Vector Auto Regression) model introduced by [36], which examined the dynamic relationship between crude oil prices and the USD exchange rate within the structural break detection context.

The integration of renewable energy sources in the energy mix gradually reduces dependence on fossil fuels, resulting in more environmentally-friendly economic growth. Therefore, the role of renewable energy sources is contributing significantly to climate change mitigation while their use has attracted significant scientific interest, with the assistance of different methodologies and for different research areas [37–43]. In most cases, and based on the existing literature, the use of renewable energy sources is an effective means for a reduction in carbon emissions and climate change mitigation in sequence [44–49].

Another determinant of the economic growth/energy consumption relationship is globality since it functions as a mechanism for achieving economic growth via international trade, foreign direct investment (FDI), and connection with other economies. However, the environmental impacts associated with globalization based on contemporary literature are ambiguous [50–52].

The issue of three pillar sustainability is an utmost priority for the firms since stakeholders and policymakers have imposed this principle in order to confront challenges arising due to modern conventional industrial practices and regulations. The sustainability issue in a corporate strategy has become a necessity, while the modern literature has validated the contribution of sustainable practices to the economic success of an organization [53–55]. The concept of sustainable practices incorporates all aspects of activities, including social, economic and environmental dimensions [54,55], while different indices have been used not only for sustainability but also for corporate financial performance, as reflected in the indices ROA and ROI [6].

More specifically, the majority of the existing literature has suggested that the adoption of green practices may affect not only the short-term financial performance but also the long-term profitability of different industries [56,57].

A number of different methodologies for firms of different sectors has been a subject of study for corporate environmental responsibility and financial performance association [57]. The majority of the existing literature has validated a positive relationship while a small proportion has confirmed either negative or no linkages at all. In the short term, an index for financial performance that has been employed has been either the Tobin Q, the Return on Equity (ROE), or the economic value added (EVA) margin. A positive relationship was confirmed by [58–61]. This relationship is affected by different microeconomic and macroeconomic factors, including the business stage or the regional economic development [58].

The relationship might also be reversed and, more specifically, to focus on the impact of financial development on corporate strategy concerning the adoption of green practices. The existing literature has confirmed that an improvement in the financial system may also well improve the environmental quality since particular firms may adopt energy-efficient and eco-innovative production methods [62,63]. The declining production cost, enhancing product competitiveness, the use of energy-efficient technology and the control of energy cost may well serve as means for the establishment and maintenance of this relationship [62–64].

The present manuscript makes an effort to identify and quantify a relationship between corporate financial performance in global terms and environmental performance by using, as a proxy, the volume of carbon emissions, while in the model estimated, we incorporated the EUR/USD exchange rate as well as the Baltic Clean Dry Index. The particular index is related to tankers that carry oil products by sea. Therefore, it denotes the carriage of the oil cargo by the sea, which in the sequence, is reflecting the energy consumption and raw materials used in industry to produce goods. Based on the above, the particular index can be used as a proxy for the trend of the global industry. The indices used for the present work may fill a gap in the existing literature for the study of financial development–renewable energy–environmental degradation association.

3. Data and Methodology

The present work, as mentioned above, intends to investigate the interlinkages between carbon emissions (CO_2), the financial index denoted as Environmental Opportunities All Shares of the firms in FTSE (FTEOAS), the EUR/USD exchange rate and, finally, the last variable, which is the Baltic Clean Tanker (BAIT).

The FTEOAS financial index was used as a proxy for the economic performance of environmentally friendly firms since this index includes companies that have at least 20% of their business derived from environmental markets and technologies.

The EUR/USD exchange rate was used as it strongly affects global economic growth. With the use of the above exchange rate, the isolation of growth factors related to the world foreign exchange markets was achieved. Carbon dioxide and economic growth are closely related [65].

In order to capture the interlinkages of the variables presented above, the following empirical function was formulated:

$$f\ (CO_2\ t, BAIT, EUR\_USD, FTSE) \tag{1}$$

The particular model aims to unveil the impact of lean energy use, and financial development based on green technologies as synopsized in FTSE EO on carbon dioxide emissions and vice versa. The findings may confirm or reject the technology's environmental performance.

All the data were monthly, and the reference period extended from November 2005 to August 2020. The limitation in the time periods is related to the novelty of the FTEOAS index since it was introduced in the year 2005. The data used were derived by Reuters. The transformation in logarithmic form preceded the data process.

The following graph (Figure 1) illustrates the evolution of all the variables employed in the analysis.

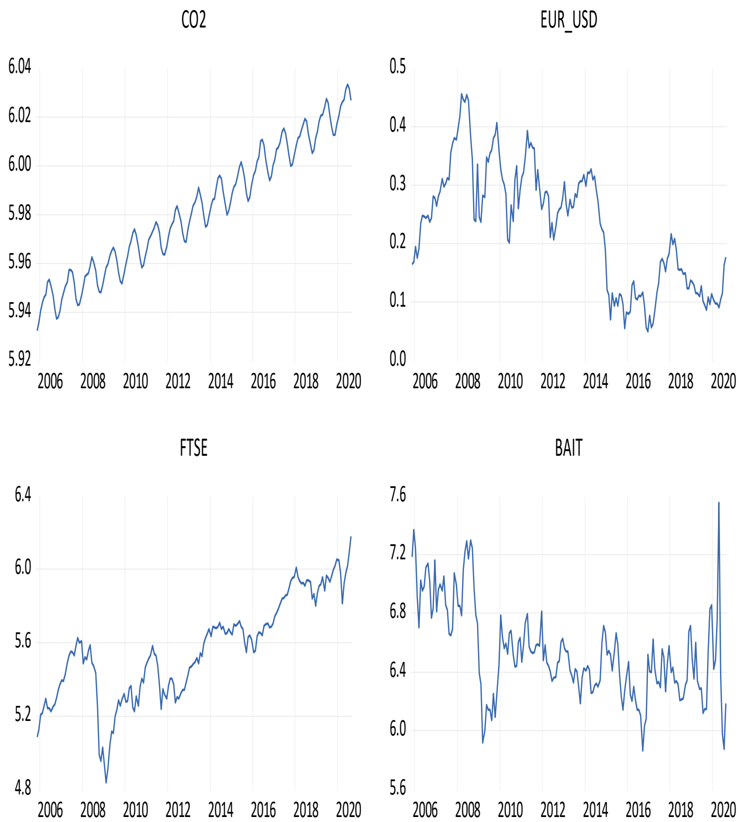

Figure 1. The evolution of the model variables.

Prior to the model estimation and the presentation of the methodology employed, we conducted unit root tests in order to test the integration rank of each variable, and to be more specific we used the break unit root tests. Regarding the methodology used, as already mentioned above, it was the Bayesian VAR. Within the last decade, the VAR models have been extensively used. The outperformance of VAR models in macroeconomics has been stressed in the literature, until recently [66]. Their simplicity enhances the ability of the models to capture dynamic linear relationships between time series without imposing restrictions on parameters as in structural VAR models. However, numerous problems arise in the process of VAR estimation. Firstly, a typical VAR model performs more efficiently with a small number of variables. More specifically, there is the risk of 'overfitting' in the case of many parameters (risk is present also with moderate size), since the ability to estimate the abundance of unrestricted parameters is limited. In addition, the models to be estimated based on VAR methodology may suffer from omitted variable bias since only a few variables are included, making the models poor in forecasting and in structural analysis ability [67,68]. What is more, the VAR approach suffers from the loss in the degree of freedom arising from the lag length size, with significant results in the reliability of the parameters' point estimations.

Having taken into consideration all of the above, along with the small sample data available, we employed a B-VAR model to provide better results than the classical VAR model.

The B-VAR model presents several advantages. First, the priors enhance the achievement of better results without the implementation of restricted models (i.e., models with many coefficients set to zero). Specifically, the posterior distribution in the Bayesian approach was based on a combination of information derived by the sample along with the researchers' prior information on the coefficients (priors). The prior selection determined the data ability to provide plausible results. The researchers set the prior according to the information they provided, and the nature of the parameters to be estimated, while the informative priors may well reflect the authors' perceptions.

Our limited sample data amplified the use of the B-VAR model, while its estimation was based on the Minnesota prior specification, incorporating all the valuable information in the parameters' estimations. The methodology employed was intended to unveil the interlinkages between CO_2, the FTEOAS, EUR/USD and BAIT.

The methodology used to estimate the posteriors was the maximum likelihood function since it outperforms other methodologies, such as the Generalized Method of Moments. The particular methodology was introduced by [69], allowing more accurate estimations.

The application of the Bayesian method to VAR models enabled the generation of a tractable posterior with the same density function of the prior [70]. In our study, we employed the Litterman/Minnesota prior for the target parameter, which is a normal prior, assuming that the value of the prior is determined by the value of the hyperparameter μ that is set close to zero, with non-zero being the covariance prior, having estimated the matrix of error terms, under the assumption that the variance–covariance matrix is diagonal where all coefficients, except their own lags (and a possible constant), are equal to zero. In the next step, we specified the prior covariance for the target parameter, considering a set of hyperparameters [71]. The hyperparameter selected, namely $\lambda 1$, was set to a small value, wanting to underline that the prior information outperforms the sample information. What is more, the second hyperparameter, $\lambda 2$, determines the lag significance of the other variables, while the parameter $\lambda 3$ regulates the impact of the exogenous variable in the model. Finally, $\lambda 4$ reflects the data differences in the scale and variability, while in the case that $\lambda 4 = 1$, the lag decay is linear, while it is harmonic or geometric if $\lambda 4 > 0$ [72].

Within the framework presented above, we computed the impulse response functions (IRFs) and the forecast error variance decomposition functions (FEVDs) and evaluated the forecasting performance. The two-lag selection for the B-VAR model estimation was based on the Schwarz Bayesian criterion [73].

4. Results

4.1. Descriptive Statistics

Prior to our data analysis, we calculated the descriptive statistics of all the variables employed, which are provided in Table 1. Evidently, the variable with the smaller value is the EUR/USD exchange rate, while the greater value is recorded for the BAIT variable.

As far as the deviations are concerned, the smaller value can be observed for CO_2, while the greater one is for the BAIT. According to the Jarque–Bera values, the null hypothesis of residuals normality was rejected for all variables, except FTEOS. Regarding correlation, there was a positive correlation between CO_2, and FTEOAS, whereas for all other variables, CO_2 was negatively correlated. Correlation among variables was tested in order to examine for high multicollinearity.

Table 1. Descriptive statistics and correlation matrix.

Variables	FTEOAS	CO_2	EUR/USD	BAIT
Mean	5.561	5.982	0.23	6.534
Maximum	6.18	6.033	0.456	7.556
Minimum	4.838	5.932	0.05	5.864
Std.Dev	0.276	0.026	0.103	0.318
Skewness	−0.105	0.123	0.091	0.642
Kurtosis	2.459	1.92	2.005	3.235
Jarque–Bera	2.495	9.092	7.596	12.635
Correlation matrix				
FTEOAS	1			
CO_2	0.840839	1		
EUR/USD	−0.518093	−0.699190	1	
BAIT	−0.285527	−0.537993	0.321132	1

4.2. Break Unit Root Tests

The tests employed in order to identify the rank of integration for the variables used were the break unit root tests. The results of the tests are synopsized in the following Table 2.

Table 2. ADF break unit root results.

Variables	ADF Break Unit Root	Break Date
FTSE	−2.8 (0.2)	2013M06
ΔFTSE	−12.8 *** (0.000)	2008M10
BAIT	−2.89 (0.10)	2018M11
ΔBAIT	−13.83 *** (0.00)	2009M04
CO2t	−1.18 (0.9)	2006M6
ΔCO2t	−5.66 *** (0.00)	2006M05
Euro/Dollar	−4.36 (0.10)	2014M07
ΔEuro/Dollar	−14.6 *** (0.00)	2008M10

*** reject of unit root test for 1% level of significance with critical values −4.94, −4.44, −4.19 for 1.5 and 10% level of significance.

Based on our findings, all the variables are I (1), namely nonstationary in levels and stationary in first differences. Thus, all the variables may provide reliable results for a VAR model estimation.

4.3. Impulse Response Analysis

The next graph (Figure 2) presents the IRF for the B-VAR model including all the variables employed. The regions included in the red dotted lines indicate the posterior confidence intervals for the 5% level of significance derived through standard percentile bootstrap using 999 iterations.

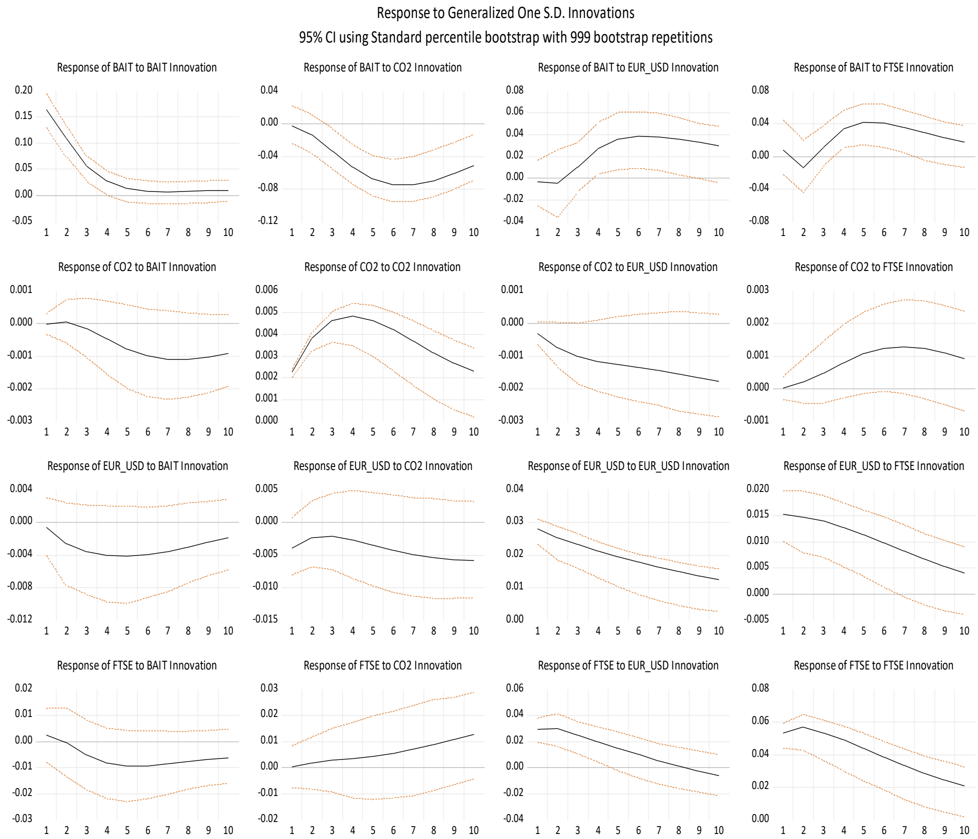

Figure 2. Impulse Response Analysis of the model variables for a ten−period time horizon.

More specifically, Figure 2 illustrates the responses of a variable to a shock (one standard deviation) from each of the other variables for the B-VAR model until ten periods. This is the time when this effect becomes less significant. This figure unveils the interlinkages between FTSE, BAIT, CO_2 and the EUR/USD exchange rate. In addition, we validate the directions of causality; as a robustness check, the horizon of the IRFs may be extended from ten to twenty years.

Based on our findings, a shock in the exchange rate seems to affect carbon emissions being generated in a negative way, reaching the minimum value in period six, while stability is evident for the remaining years. On the other hand, a shock in FTSE seems to positively affect the carbon emissions after the second period, while its effect seems to decay after the ninth period. As far as BAIT is concerned, a shock in the particular variable seems to result in a decrease in carbon emissions, while a return to a stable state is evident after period ten. A shock in the EUR/USD exchange rate seems to affect carbon emissions in a negative way but the FTSE index in a positively one. Both responses are linear and seem to decay after period nine. Another significant finding is the limited effect, but of similar pattern, which causes a shock in the BAIT to the exchange rate and FTSE.

What is more, a shock in carbon emissions affects the FTSE and BAIT behavior in a different way. More specifically, FTSE seems to respond with an increasing linear trend, while the response of BAIT is nonlinear, and with the decreasing trend being followed by an increasing one and becoming stable after period nine. Last but not least, the response of FTSE and BAIT on a shock in the EUR/USD exchange rate should be mentioned. An initial increasing rate in FTSE in the first two periods is followed by a decreasing rate for the remaining periods. The opposite pattern is evident for the BAIT variable.

In order to test the robustness of the results, we re-estimated the IRFs for twenty time periods since stability is evident in the following graph (Figure 3).

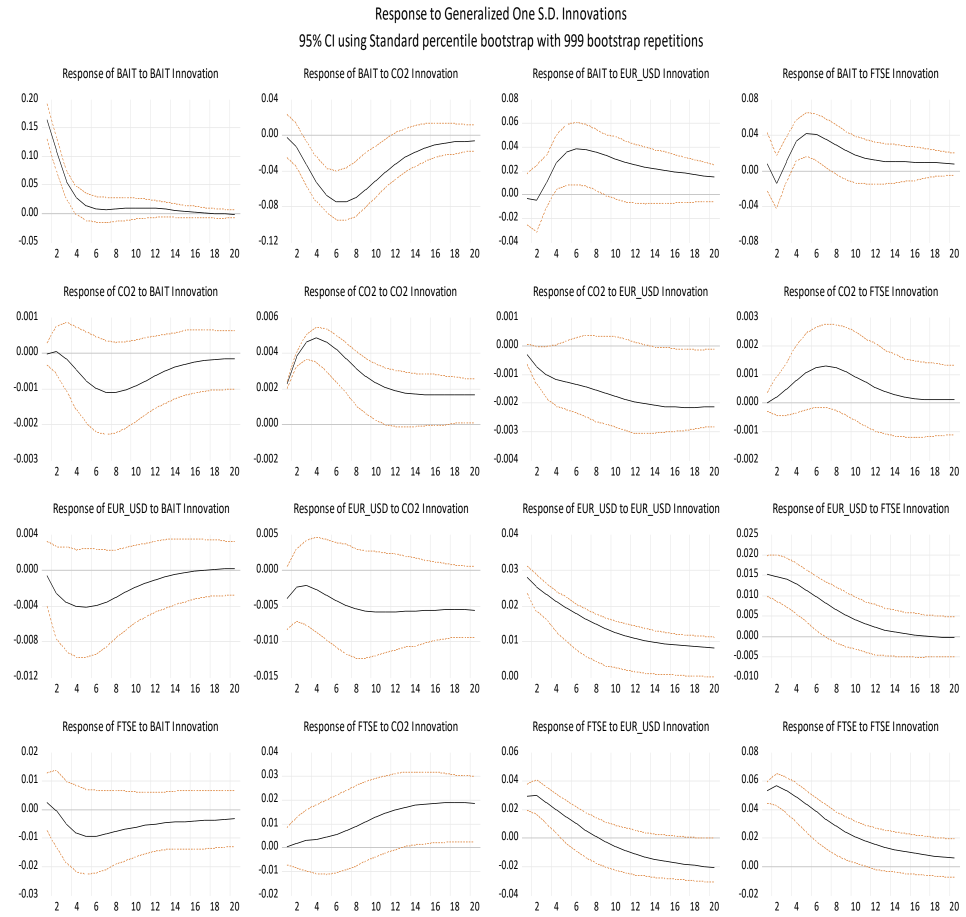

Figure 3. Impulse Response Analysis of the model variables for a twenty−period time horizon.

As can be seen in all graphs, stability has been recovered after the tenth period.

4.4. Variance Decomposition Analysis

Another step in our analysis involved the results provided in the following table (Table 2). Evidently, the forecast variance of carbon emissions was little related to the exchange rate (at about 5%), which was an expected result. What is more, the FTSE may have interpreted almost 20% of the carbon emissions. The most significant finding in the present study involved the variance of carbon emissions that was attributed to the BAIT index. More specifically, the variance was interpreted with an increasing rate along with the time. Namely, after ten periods, BAIT interpreted almost 38% of carbon emission variance, while in the first periods, this was extremely limited. As far as the financial index interlinkages are concerned, in most cases, the variance decomposition of each index (FTSE, BAIT) attributed to the other (BAIT and FTSE, respectively) was less than 10%. As far as the role of the EUR/USD exchange rate in the variance of FTSE and BAIT is concerned, it was less than 5%, which was another finding that needs to be interpreted. All the results will be discussed, and the conclusions will be provided in the next section.

The forecast error variance decomposition function (FEVDs) was a necessary step in our analysis for acquiring an insight into the significance of each variable in affecting the other variables of the model.

Last but not least, part of the methodology is the forecast error variance decomposition functions (FEVDs), which was a necessary step in our analysis for acquiring an insight into the significance of each variable in affecting the other variables of the model [74].

The results are provided in the following table (Table 2).

Evidently, and based on our findings, the role of all the variables of the study on the carbon emissions is of limited significance, though in the last periods, this impact seemed to increase more for the case of FTSE OE and less for BAIT, while the exchange rate affected most of the variables under review. Furthermore, the role of carbon emissions on the variability of FTSE and BAIT seemingly played a very important role, which acted in an augmentable way while the periods passed. For instance, in the tenth period, the carbon emissions interpreted almost 5% variability of BAIT and 1.5% of FTSE variability. The reversed causality was not of the same value, namely BAIT and FTSE interpreted 5% and 0.1% of the variability of carbon emissions, while in the case of twenty periods, the impact became more intense for all the interlinkages among the variables.

4.5. Forecast Evaluation

The next step in our analysis involved the performance of our model evaluations. More specifically, this section provides the forecast accuracy performance for two different VAR specifications (unrestricted VAR model and B-VAR models) based on our dataset, as described in a previous section. The comparison of the forecast accuracy was achieved by computing the point forecasts (ten periods ahead), namely the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). The formula for those indices is given below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n}} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \overline{y}|}{n} \tag{3}$$

The selection of those two forecast accuracy measures was based on their sensitivity to great and small deviations from the true values. The calculation results are provided in the following table (Table 3).

Table 3. Forecast Variance Decomposition (FVD) for a ten-time period horizon.

	Variance Decomposition of CO_2			
	CO_2	**BAIT**	**EUR_USD**	**FTSE**
1	99.99851	0.000656	0.000653	0.000180
2	99.99814	0.000580	0.001143	0.000140
3	99.99620	0.001032	0.002656	0.000110
4	99.99104	0.003798	0.004947	0.000218
5	99.98302	0.008771	0.007766	0.000439
6	99.97283	0.015522	0.010920	0.000729
7	99.96107	0.023619	0.014265	0.001048
8	99.94825	0.032685	0.017696	0.001365
9	99.93480	0.042409	0.021134	0.001661
10	99.92101	0.052538	0.024525	0.001922
	Variance Decomposition of BAIT			
	CO_2	**BAIT**	**EUR_USD**	**FTSE**
1	0.000647	99.93214	0.015436	0.051777
2	0.000654	99.91684	0.025692	0.056810
3	0.001733	99.77655	0.105224	0.116494
4	0.003985	99.50796	0.263561	0.224493
5	0.007670	99.12614	0.493223	0.372966
6	0.013077	98.64980	0.783032	0.554091
7	0.020494	98.09796	1.121127	0.760414
8	0.030194	97.48907	1.495812	0.984923
9	0.042422	96.84040	1.896014	1.221163
10	0.057394	96.16763	2.311618	1.463356

Table 3. *Cont.*

	Variance Decomposition of EUR_USD			
	CO_2	BAIT	EUR_USD	FTSE
1	0.000654	0.014649	94.76806	5.216632
2	0.000659	0.014182	94.79656	5.188596
3	0.006936	0.015148	95.14940	4.828514
4	0.021941	0.016634	95.54341	4.418015
5	0.046354	0.018642	95.91371	4.021290
6	0.080505	0.021243	96.23763	3.660617
7	0.124579	0.024519	96.50494	3.345967
8	0.178658	0.028552	96.71039	3.082398
9	0.242736	0.033423	96.85135	2.872494
10	0.316728	0.039204	96.92673	2.717343
	Variance Decomposition of FTSE			
	CO_2	BAIT	EUR_USD	FTSE
1	0.000170	0.049195	5.217315	94.73332
2	0.000168	0.047846	5.299099	94.65289
3	0.000270	0.032546	5.022295	94.94489
4	0.001029	0.036463	4.676703	95.28580
5	0.002458	0.063534	4.324008	95.61000
6	0.004457	0.111371	3.984949	95.89922
7	0.006908	0.176386	3.668583	96.14812
8	0.009690	0.255025	3.379385	96.35590
9	0.012691	0.344100	3.119598	96.52361
10	0.015806	0.440854	2.890201	96.65314

The aforementioned results provided in Table 4 suggest a good performance for our model.

Table 4. B-VAR forecast statistics of the different prior distributions for the model variables.

Variable	RMSE	MAE
BAIT	0.286360	0.218674
CO_2	0.015130	0.012809
EUR_USD	0.077399	0.062435
FTSE	0.204974	0.154078

Notes: The table shows one-year ahead and two-year ahead forecasts. RMSE: root mean square error; MAE: Mean Average Error.

5. Discussion

The economic performance/environmental degradation relationship has been the subject of extended research with different methodologies and conflicting results, with research areas being either isolated countries or groups of countries [49–52,60–66]. In addition, the role of energy seems to be highly important in the economic growth/carbon emissions interlinkages, while there are two strands of literature. More specifically, a few studies investigate the relationship between energy consumption and real income growth [75–90], while others test the validity of the Environmental Kuznets Curve hypothesis, which examines the relationship between GHGs and real income growth [81].

It is a stylized fact that extensive CO_2 and economic growth are closely related, while the role of financial and stock markets in economic growth cannot be neglected, given that in global terms, a stock market and financial index such as FTSE is a reliable proxy for economic growth [52]. However, what has not been studied until now is the behavior of economic firms focusing on renewable energy, such as those included in FTSE Environmental Opportunities All Shares, since they are considered environmentally-friendly firms, while the BAIT variable corresponds to the Baltic Clean Tanker, representing global economic activity based on cleaner energy sources. Thus, the present work focused on this empirical framework with the assistance of financial indices, namely BAIT, FTSE EO, exchange rates as proxies for economic growth generated by environmentally-friendly corporates and carbon emissions employed as a proxy for environmental degradation.

The variables along with the Bayesian VAR methodology employed constituted the novelty in this study. Actually, the concept is novel since we made an effort to see how the economic performance of environmentally-friendly firms (FTSE EO) and global economic activity based on cleaner energy (BAIT) are affected or affect carbon emissions, while the exchange rate captured the stock and financial market particularities.

Our findings, first of all, confirm the interlinkages among the variables studied. This result was validated with impulse response analysis as well as with variance decomposition and FEDV analysis.

More specifically, based on impulse response analysis, the response of carbon emissions on a shock affecting the exchange rate, at least in the short term, was negative, but positive for the case of FTSE open shares and negative for the case of BAIT; this reflects the fewer pollutant energy sources involved. The results found are in line with common sense since an increase in carbon emissions will increase the value of corporates specialized in energy sources and this will be reflected in the FTSE open shares. This could be explained by the fact that FTSEOAS is an indicator that measures the performance of global companies that have a significant involvement in environmentally-friendly business activities, which come along with carbon emissions while it contradicts the school of thought supporting that financial development promotes sustainable development as argued by [67]. Another important finding was the return to the steady state after nine or ten periods. This means a zero effect of BAIT on carbon emissions in the long run, which can be explained as follows: The fact that BAIT reflects global economic activity based on cleaner energy sources and its relation to carbon emissions (zero effect in the long run) may well be attributed to the fact that technological progress and the gradual replacement of the use of oil and gasoline by renewable sources and gas outperforms the initial impact of BAIT on carbon emissions.

This result is also related to the global environmental agreements since, along with the global economic conditions and the energy resources, they may well lead to the limitation of carbon emissions, formulating an effective climate change mitigation strategy.

Explicitly, climate change may well affect financial performance and more specifically stability through various channels. Physical risks arising from climate and weather events, liability risks related to demanded compensations due to loss or damages and, finally, transition risks related to the process of adjustment towards a low carbon economy may have multiple impacts on financial stability. The last type of risk is caused, in other words, by changes in the value of a large range of assets as costs and opportunities due to changes in policy, technology and physical risks [81].

Another issue that should be underlined according to our findings is the new strand of literature being born, related to the financial development/environmental degradation relationship, and how to confront the tragedy of the horizons since the impacts on financial stability can be seen later than the duration of the business cycle, the political cycle and the horizon of technocratic authorities [69].

Similar results were derived by the variance decomposition analysis and Future Error Variance Decomposition as introduced by [70].

In the reverse situation, i.e., an increase in the carbon emissions, as illustrated in Figure 3, was followed by an increase in the financial index, a result that validates the investors' interest for renewable energy as a means of climate change mitigation. As far as the reaction of the other index that reflects the global economic activity in terms of cleaner energy sources, there was a decline with an increasing rate that, after the fifth period, vanished, while the tendency to a return to the steady state was evident in the next periods. This behavior is interpreted as follows: An increase in carbon dioxide emissions makes it imperative to take action and change policy at a global level in order to achieve a shift towards cleaner, more environmentally-friendly forms of energy, with the ultimate goal of reducing emissions.

Investors are turning their attention to renewable sources due to the increase in pollutants and forecasting the political decisions that are expected to be taken. In some previous studies, different results were derived that validate no causality between the variables CO_2 and RES, a result that may be attributed to the fact that they employed variables representing real energy and not in terms of financial performance [38,71].

In addition, carbon emissions seemed to affect the exchange rate, which is an interesting finding and was related to the energy exchange among countries. More specifically, a slight decrease is recorded, which, however, was persistent for the first ten periods. The impact of the exchange rate on carbon emissions was positive or negative, depending on the country's trade structure [72,73]. The CO_2–EUR/USD exchange rate relationship is significant since both indicators are both directly and indirectly related to each other. More specifically, the negative relationship between CO_2 and EUR/USD is justified based on the following: the dollar is the leading currency in the global economy and, therefore, a major determinant of global economic growth in real and financial markets, a fact that may provide a plausible explanation for its relationship as identified with CO_2.

Furthermore, our findings validate the interlinkages among the EUR/USD exchange rate and the financial index employed, which was an expected result. More specifically the FTSE EO decreased for the first ten periods with a given rate. However, in the case of BAIT, the initial decreasing rate was followed by an increasing rate, resulting in the return to the steady state that became evident in the tenth period. Last but not least, the impact of FTSE OE and the EUR/USD exchange rate to the BAIT index seemed to have an identical pattern. More specifically, a sharp decrease within the first two periods was followed by a non-linear increasing pattern in the aforementioned variables, illustrated as a curve with a tendency of the impact to become permanent and stable after ten periods.

All the results presented above confirm the existence of interlinkages (of limited extent) among the variables studied, a result that is not in line with the work of [74], who validated the limited impact of financial development on carbon emissions in developed countries.

Previous studies have mentioned that economic expansion leads to a deterioration in the quality of the environment [12]. Moreover, complementarity between economic and environmental prosperity can be assumed to take place through the technical impact that argues that in the later stages of development, technological innovation facilitates economic growth without adversely affecting the environment [15,91].

6. Conclusions

In the present study, a Bayesian VAR model was employed in order to identify the interlinkages among the CO_2, FTEOAS, EUR/USD and BAIT variables.

The validation of interrelationships among CO_2 and financial indices (namely BAIT and FTSE OE) is a result that is in line with the existing literature [90–94].

The identification of interlinkages and causality among the variables based on the findings of impulse response and variance decomposition analyses may well provide investors and policy makers with the appropriate tools to promote ecoefficiency globally. Adopting a "polluter pays" mechanism and convincing investors and firms to adopt renewable energy along with the extended use of clean, environmentally-friendly technology are the necessary policy tools to promote economic growth at both the micro and macro level without deteriorating the quality of the environment.

Having confirmed the interlinkages among the variables, the policymakers should promote green investments along with the extended use of green energy. One of the measures that should be adopted for the promotion of green energy is subsidies. The green investments on energy are characterized by high initial cost. Thus, subsidies provided at the beginning phase of these projects ease the survival of the green companies since scale economics are formed in the initial stages and further developed in later stages.

For the case of multinational firms (as the majority of FTSE), green investments should be promoted initially in developed countries since high environmental performance adds significantly to their corporate financial performance. In the second stage, having acquired the knowledge and experience of green investments, multinational firms may consider promoting green strategies in emerging markets [58].

Last, but certainly not least, the specific findings may provide the scientific community with evidence of the critical situation on the horizon. Implicitly, climate change impacts act beyond the business cycle, the political cycle and the horizon of technocratic authorities, making the reaction to mitigation a difficult task, since the impacts on financial stability will be irreversible.

A limitation of the present work is the data span, though the methodology employed limits the robustness of our findings. Furthermore, a subject of future research could be the examination of other parameters (e.g., ESG criteria) or a comparison of specific countries/groups of countries, in order to test if the above-mentioned results are robust, not only at a global but also at a country level.

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Abbreviations

FTSE EO	Financial Times Stock Exchange Environmental Opportunities Index Series
BAIT	Baltic Clean Tanker Index
BVAR	Bayesian Vector Autoregression Model
CO_2	carbon emissions
CH_4	methane
N_2O	nitrous oxide
IRFs	impulse response functions
FEVDs	variance decomposition functions
EKC	Environmental Kuznets Curve hypothesis

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